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# BIM, 3D Cadastral Data and AI for Weather Conditions Simulation and Energy Consumption Monitoring

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**Abstract:** This paper is part of an ongoing research study on developing a methodology for the low-cost creation of the Digital Twin of an urban neighborhood for sustainable, transparent, and participatory urban management to enable low-and middle-income economies to meet the UN Sustainable Development Agenda 2030 successfully and timely, in particular SDGs 1, 7, 9, 10, 11, and 12. The methodology includes: (1) the creation of a geospatial data infrastructure by merging Building Information Models (BIMs) and 3D cadastral data that may support a number of applications (i.e., visualization of 3D volumetric legal entities), and (2) the use of Artificial Intelligence (AI) platforms, Machine Learning (ML), and sensors that are interconnected with devices located in the various property units to test and predict future scenarios and support energy efficiency applications. Two modular platforms are created: (1) to interact with the AI sensors for building tracking and management purposes (i.e., alarms, security cameras, control panels, etc.) and (2) to analyze the energy consumption data such as future predictions, anomaly detection, and scenario making. A case study is made for an urban neighborhood in Athens. It includes a dynamic weather simulation and visualization of different seasons and times of day in combination with internal energy consumption.

**Keywords:** BIM; AI; 3D cadastral data; sensors; urban neighborhood simulation; dynamic weather conditions simulation; energy consumption; future scenario making; modular platforms; low-cost

check for updates

**Citation:** Andritsou, D.; Alexiou, C.; Potsiou, C. BIM, 3D Cadastral Data and AI for Weather Conditions Simulation and Energy Consumption Monitoring. *Land* **2024**, *13*, 880. https://doi.org/10.3390/land13060880

Academic Editors: Abbas Rajabifard, Reinfried Mansberger, Eva Maria Unger and Abdullah Kara

Received: 15 April 2024
Revised: 7 June 2024
Accepted: 14 June 2024
Published: 18 June 2024

## 1. Introduction

Modern urban environments are characterized by interconnected facilities, complex systems, and overlapping networks which require constant monitoring, dynamic visualization, and thorough registration. This can be achieved through DT technology which virtually recreates a physical entity, enabling its constant monitoring and management, as well as updates in real-time. Urban DTs support sustainability and decision-making for better quality of life, disaster prevention, and management, thus covering a plethora of the SDGs of the UN Agenda 2030.

This research paper presents an innovative, multiscale, and low-cost methodology for creating a simulative DT of an urban neighborhood, concerning urban sustainability and prosperity for both the present and future. A geospatial data infrastructure is created that entails the BIMs of the neighborhood. BIMs of the outer shell of existing buildings are created by utilizing open data such as the Official Cadastral Orthophotos, Google Earth Pro, and Streetview [1], while BIMs of new buildings are modeled by utilizing available 2D architectural and floor plans as well as cross-section diagrams. The more detailed BIM modeling of both existing and new constructions is currently under investigation. Several low-cost methods (such as the use of iPhone scanning and crowdsourcing, etc.) are tested in order to achieve the internal structuring and visualization of legal entities, mainly for existing constructions. This will allow the use of the methodology for creating the necessary geospatial data infrastructure to support the creation and operation of a DT in urban areas with long-existing 3D old constructions where floor plans are not available and the cost of creating BIMs and DTs with conventional surveying methods for the neighborhood is high.

Part of the methodology is developed in an earlier paper [2], including the 3D modeling of Restrictions such as an underground sewer system and road network in the geospatial data infrastructure. The various property units (private and common) are visualized as 3D volumetric prisms for the buildings of the neighborhood under study. AI-generated sensors, platforms, and ML algorithms are created in this paper to be used in energy efficiency applications for simulating, predicting, and providing suggestions for household energy consumption management by the owners, as well as expense minimization, in order to optimize the overall environmental footprint of each building. At its current stage, the methodology links 3D cadastral information with BIM 4D energy consumption data (time and season), 5D cost information, and 6D (sustainability) construction management. The research proposes a low-cost and easy solution for the creation of a neighborhood DT that can be used for general urban management purposes (either by the residents or by the authorities), particularly for real-time energy consumption monitoring and intervention (owners/users may have the option to manage the various MEP and HVAC devices from a distance). In order to check the methodology, open-source weather data for the neighborhood are used to create AI-generated sensors for all property units in the neighborhood to create constant realistic datasets based on the location of the neighborhood, time of day, and real weather conditions. An extensive simulation of an urban neighborhood is the final outcome of this research.

This contribution may support optimal urban management, push 3D cadastral incentives forward, foster sustainable development, tackle environmental challenges, establish social equality, and boost the economic growth of urban settlements, thus dealing with SDGs 1 (No poverty), 7 (Affordable and Clean Energy), 9 (Industry, Innovation, and Infrastructure), 10 (Reduced Inequalities), 11 (Sustainable Cities and Communities), and 12 (Responsible Consumption and Production). The research is also expandable regarding the new Land Administration Domain Model II (LADM II) standard (revision of ISO 19152:2012 [3]) as the DT simulative model can implement an .xml LADM database schema. The revised LADM II is a multipart standard with renewed land registration and spatial plan information, amongst others. At the same time, it hosts 3D spatial profiles that support the full lifecycle of 3D objects, as well as fostering the 3D representation of RRRs derived from public and private law. The paper also aims to contribute to broadening the frontiers of research regarding spatial data science for obtaining, analyzing, and visualizing economic and environmental data related to construction. It is anticipated to present a new geospatial paradigm merged with AI and ML for dealing with spatiotemporal remotely sensed data. The multiscale nature of the proposal and its interoperable technology make it compatible with the principles of Agenda 2030, as well as the LADM II standard.

## 2. State of the Art

DT technology, regarding the built environment, utilizes digital models for simulations and facility management [4]. A DT is the cyber twin of a real-world element such as a building, neighborhood, or city. Hypothetical scenarios, optimal proposals, and immediate solutions can be provided through DT technology while simulations can be executed. DT provides real-time connection between an entity in the real world and its cyber reformation, thus contributing to optimal energy tracking, prediction making, and minimizing resource consumption [5,6]. Other perceptions of a DT present it as an absolute virtual counterpart of an asset that simulates all of its behaviors, actions, and attributes through digital models [7]. DTs can be built on the premise of enriching a BIM with information about the cost estimation, energy expenditure, operation, and functionality of its entailed devices [8].

BIM technology is the foundation of DT, as after proper configuration, it can enable monitoring through a central collaborative network [9]. DT is, after all, regarded as the advancement of BIM [10]. BIM technology offers detailed 3D model visualization [11] and aids construction procedures [12] while enhancing interoperability and communication between the various stakeholders of the Architecture, Engineering, and Construction (AEC) sectors [13]. BIM can also help with sustainability projects [12]. BIM can also assist with resource savings and the optimal management of an asset throughout its lifecycle, serving as a 3D detailed hub for storing various information such as cadastral, land use, fiscal, environmental, structural, architectural, topographical, mechanical, geometrical, etc.

DT constructs a virtual real-time 3D visualization of a real-world entity, enriched with field sensors that enable dual-ended communication between the virtual and physical environments [14]. It offers simulations, real-time interventions, live monitoring, and immediate detection of problems or failures [15]. DT technology can provide valuable help in simulating, testing, and designing various urban planning scenarios and alternatives [16]. It has been stated that one of the biggest sectors that DT technology can contribute to has to do with maintaining and supervising various built and urban operations and facilities [17].

The importance of BIM has been highlighted as a new standardized medium that can contribute to the construction, land management, cadastral, and sustainability sectors. BIM applications regarding 4D research have been developed to boost the efficiency of construction projects [18]. A BIM-based safety tool for detecting errors and waste in construction sites has also been developed [19]. The role of BIM in optimal energy management and building operations has also been extensively researched [20]. Practical paradigms of BIM-enabled decision-making have been studied for the construction stages of buildings in order to design and compare different scenarios [21]. IFC is a capable data format for suitability and energy simulations, as has been shown in various cases [22]. BIM has also been studied under the prism of 3D cadastral and land management applications. A BIM/IFC proposal merged with the international cadastral standard of LADM (Land Administration Domain Model) has been constructed for the 3D visualization of complex legal entities as volumetric prisms in one open platform [2]. The IFC schema can also be extended and properly adjusted in order to confront land management issues and cover complex legal entities in multi-story and high-rise complicated constructions [23]. Crowdsourced applications centering around BIM and 3D cadastral surveys in one homogenous open background have also been developed [24]. BIM-based queries that can extract property and ownership information have also been designed [25]. BIM can greatly contribute to reforming the current cadastral state as it offers comprehensive 3D visualization and because, as it has been stated, 2D cadastral registries fail to present the complex legal reality of modern urban structures [26].

BIM models can be interconnected with sensors, enabling constant updates and communication with the real environment. Therefore, they can be transformed into a DT that enables interaction with its devices and elements in real-time [27]. DT applications can also implement crowd-enabling incentives for more engaging land and urban management [28]. A DT can effectively contribute to diminishing gas emissions and safer transportation [29]. BIMs that are transformed through the integration of IoT networks can also contribute to indoor environment monitoring [30], controlling the interior thermal comfort of households [31] and adjusting the optimal management of the various spaces of a building [32]. An Information and Communication (ICT) platform for structuring an optimal residential building design and operation has been studied [9]. The combination of IFC and DT has also been studied thoroughly [33].

City-scaled DTs that are empowered by gamified operations have also been developed [34]. Schemas describing the ideal operation and structure of building Digital Twins have been developed, presenting a BIM model as the basis for visualization and making predictions. In addition, it can be a source of sensor data that are updated in real-time and a cloud-based inventory or database that can host the sensor-acquired information and simulative results for optimal building management [35]. Community-based DTs can also be structured with their focus being on individual elements such as the urban systems that compose an urban center i.e., transportation networks, traffic, etc. [35]. DT advancements could be supported and aided by the new rising trend in the technological department of AI that concerns multiple fields of interest such as scientific, environmental, economic, etc. AI can contribute to a plethora of sectors and has already left its impact on medical, engineering, and communication applications. AI can be merged with a wide abundance of technologies and is adjustable to many standards, providing economically responsible, quick, and smart solutions. A simulation of a city center has been made, after being properly equipped with IoT devices, for the optimal observation of all urban facilities through AI algorithms [36]. Sensors can provide vital data on humidity, temperature, etc., which can aid optimal energy expenditure [37]. IoT networks can empower optimal energy consumption and modernize the current state of things [38]. Programs that merge BIM and IoT for monitoring the thermoregulatory behaviorism of household owners have been developed [39].

Three-dimensional cadastral visualization has been widely researched for the past years as its usefulness [40] and potential user engagement [41] are two core key points that can aid in reforming current conventional cadastral methods. Crowdsourced studies have been made showcasing the importance of color and geometrical representation in proper 3D cadastral entity identification [42]. Three-dimensional visual representation of cadastral and legal entities is crucial as the 2D current methods and registries fail to thoroughly register them [26]. Three-dimensional cadastral research and applications have been constructed around the globe. Three-dimensional parcels have been represented as 3D spatial objects in New Zealand [43] while important 3D data about underground ownerships have also been collected and stored in cadastral applications [44].

The semantic connection between existing cadastral elements, i.e., parcels and 3D property elements, has been tested with various methods, including Unified Markup Language (UML) for a paradigm in Poland [45]. In Greece, crowdsourced methods have been implemented to create web-based platforms that can support the official cadastral declaration process [46]. Proposals for carrying out quicker 3D land registration processes have been made, deploying Model View Definition (MVD) standards based on the Information Delivery Manual (IDM ISO 29481) [47].

Three-dimensional cadastral applications that utilize BIM technology have also been conducted, such as extending the standard in order for it to be able to host ownership and building boundary information [48] or merging BIM with Geographic Information Systems (GISs) for storing and viewing 3D cadastral data [49], as well as implementing CityGML with IFC for 3D representation of cadastral entities [50].

This proposed methodology aims to enable:

- The creation of a low-cost 3D geospatial data infrastructure for the operation of a DT of an urban neighborhood for low- and middle-level economies;
- The management of rising energy consumption costs and natural resource waste nowadays;
- Owners/users will be able to intervene with the various devices of each household;
- Authorities will be able to provide incentives for an energy-saving policy;
- The use of AI-enabled applications in policy-making;
- The visualization, management, and tracking of the complex urban environment in one homogenous cloud-based environment.

## 3. Methodology

The methodology in Figure 1 proposes the creation of:

- BIMs of existing and new buildings of the neighborhood;
- AI-based sensors;
- An energy management and optimization platform. The user is able to: (1) predict what will happen at a certain period in the future in terms of energy consumption (according to the ML algorithm), (2) receive notifications about anomalies that have happened during a certain period of time, and (3) receive automated optimal suggestions based on real-time inputs of specific weather and environmental conditions and predetermined requirements (i.e., outer temperature, humidity, etc.);

- A synthetic IoT sensor network generator platform that creates the sensors by utilizing AI and real weather and location data, as well as enabling the user to interact with their operation in real-time.

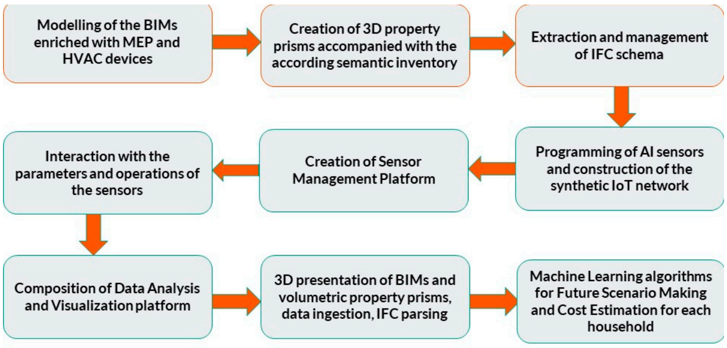


**Figure 1.** The methodology steps.

The [1] methodology is followed for the approximate creation of the external shell of the existing buildings, creating a homogenous internal space without room categorizations. For the newly made constructions, the architectural and topographical plans are used for the exact and accurate recreation of the various internal room classifications modeled for the new constructions.

The next step entails the enrichment of each BIM with the corresponding Mechanical, Electrical, and Plumbing (MEP) equipment, as well as Heating, Ventilation, and Air-Conditioning (HVAC) equipment. The MEP category entails electrical and mechanical control panels, fire and protection alarms, intercoms, toilets, bathtubs, sinks, refrigerators, stoves, washing machines, lighting, computers, displays, televisions, etc. The HVAC category consists of water heater tanks, boilers, air-conditioning units, heaters, gas providers, energy-providing units, etc. Furniture for daily life has also been added, such as sofas, beds, cabinets, chairs, tables, etc.

The following step concerns the 3D modeling phase of the various private property units and common spaces of the buildings under study. For the newly constructed buildings, the legal boundaries of each property unit should follow the legislation of the country (in this case the Greek legislation was followed as the case study is made for a Greek neighborhood), as well as the area classification of the 2D plans. For the existing buildings, it is assumed that each floor is one property unit. For the new constructions, each property unit is modeled and visualized as a volumetric prism separately.

Therefore, for each unique type of property unit, a corresponding 3D volumetric prism is created depicting the following legal rights in 3D. The private areas entail:

1. Apartments;
2. Internal parking spots;
3. External parking spots;
4. Storage rooms.

The commonly owned areas are:

1. Hallways, corridors, stairs, and elevators;
2. Boiler and bunker rooms;
3. Building entrances;
4. Penthouses.

Semantic and geometrical information is stored in the IFC files for each property space, thus creating a conceptual inventory with information about the type of property, level, area, perimeter, etc. The BIM of the neighborhood is extracted in DataSmith format from the Revit 2023 software and then inserted into the free-to-use program Twinmotion by Unreal Engine and Epic Games.

For the creation of the "Energy Management and Optimization Platform", the following elements are used:

- IoT Data Parser which receives the data from the various sensors (i.e., boilers, solar units, air conditioning units, etc.) and implements the findings in an interpreted programming language;
- Database that stores the previously mentioned time series data from the sensors as well as the parsed IFC schemas that include the sensor metadata;
- IFC Data Parser which essentially is the IfcOpenShell. This element has to do with receiving the 3D models from the users while it searches, aggregates, and filters the IFC schemas and stores the desired information in the previously mentioned Database;
- Web interface that is the result that is presented to the owners/users. The web interfaces enable the user to interact with the various sensors and more specifically manage, start, omit, classify, and store their ports. The web interface is based on the WebGL web standard for reforming, visualizing, and rendering the modelled BIMs in the cloud interface;
- ML models that include all the needed algorithms to enable future energy expenditure predictions, cost-saving suggestions, and scenario simulations for each household. These include "Data Preprocessing and Feature Engineering", "Anomaly Detection", "Forecasting", and "Decision Trees".

Through AI, the platform crafts the following sensor types:

1. Temperature;
2. Luminance;
3. Capacity;
4. Voltage;
5. Duration of operation.

A vital aspect of this methodology is the utilization of the TimeGAN network. Most IoT sensors currently in existence can use time-series formatted data in order to transmit or expose data. TimeGAN is essentially a cutting-edge generative artificial intelligence model that can replicate IoT sensors at scale, run experiments, validate programming sequences, and improve platform performances. TimeGAN is a cheap and flexible medium that produces vast time series datasets that are ideal for large-scale experimentation as they offer both qualitative and quantitative data [51]. It allows the seamless and accurate production of vast time series data, which is essential for simulating the operation of all the various household devices.

The second platform concerns the "Synthetic IoT Sensor Network Generator". This platform uses the TimeGAN generative model to produce AI-based IoT sensors with specialized attributes. The web interface allows the users to temper with the sensors and configure their numbers and types. For each sensor, TimeGAN produces realistic and simulative data based on the location and georeference of the buildings and the weather conditions of the area under study. A Generative Application Programming Interface (API) is utilized, which enables the configuration and synthetization of producing sensors. Like before, a RESTful API is utilized for the interconnection of the various components but also for communicating with the first application for energy management.

APIs are constructed so that the two individual platforms will be able to communicate with each other and also with the user, maintaining the constant flow of data. There are three distinct APIs with singular usages:

1. Data API that allows the retrieval and saving of data;
2. Model API that handles the IFC schemas and 3D BIMs;
3. Analytic API that contains the ML algorithms for energy expenditure and scenario production.

Communication between the various components is ensured by the usage of RESTful APIs based on the REST standard, which uses HTTP protocols to allow the intercommunication of different elements.

The backbone of the programming procedures is the language Python 3.11. IfcOpenShell is also utilized as it is an open-sourced library for parsing IFC files that contain metadata about sensors and data for 3D models. Three.js is a JavaScript open-sourced library that is used throughout the methodology in order to successfully reform and visualize the various modelled 3D BIMs on the web interface.

For the final implementation of this methodology for a particular neighborhood, the local weather data are streamlined to the ML algorithm "Decision Trees".

## 4. Case Study

The neighborhood under study is in the municipality of Chalandri in Athens, Greece. The neighborhood is comprised of eight complex buildings, with seven of them being multi-story residential apartment buildings (Figure 2) and the remaining one being a two-story high school with a gymnasium (Figure 3). Figures 4 and 5 show the detailed interior of the BIMs. Figures 6 and 7 present some 3D property units of the BIMs. Figure 8 shows the modeled Restrictions of the sewer system and road network [2].

**Figure 2.** BIM of a six-story residential building.

**Figure 3.** Modelled high school building.

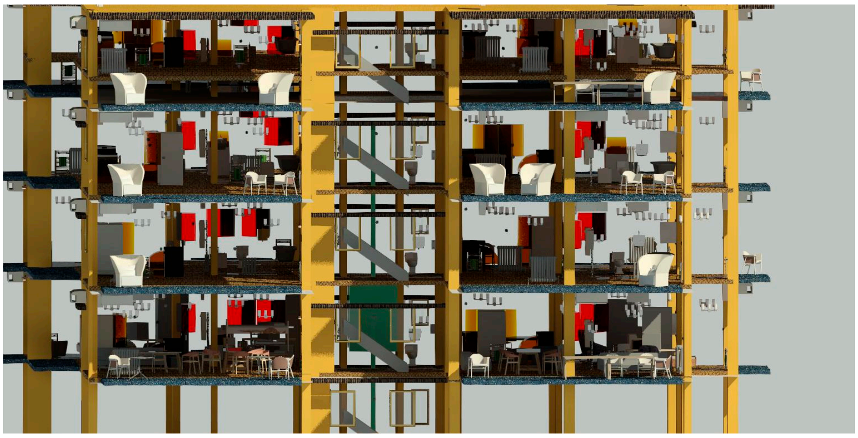


**Figure 4.** Enriched interior layout for each apartment.

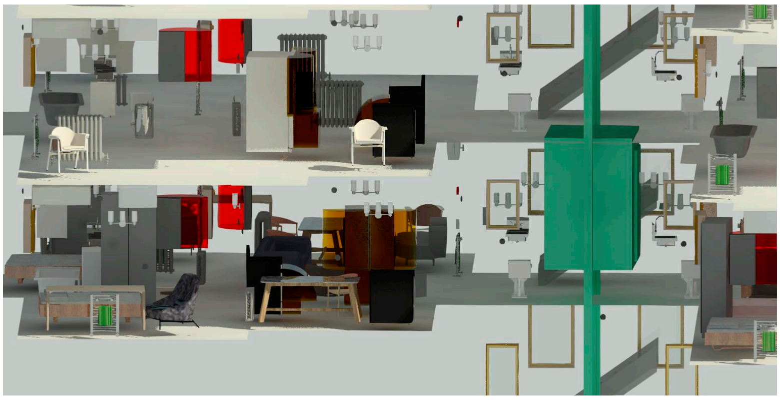


**Figure 5.** Furniture for daily life and mechanical, electrical, and plumbing equipment.

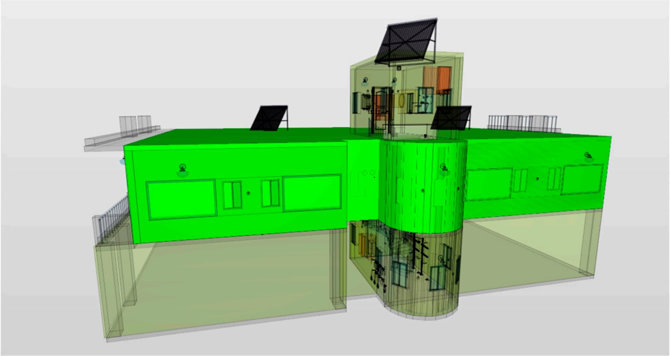
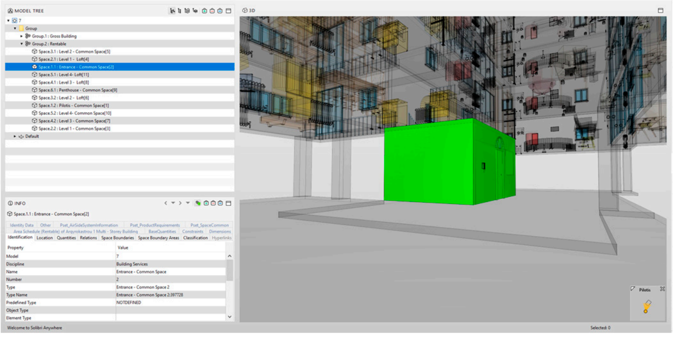


**Figure 6.** Three-dimensional property unit of a loft in the Solibri Model Viewer by Nemetschek.



7
Group
Group.1 : Gross Building
Group.2 : Rentable
Space.3.1 : Level 2 - Common Space[5]
Space.2.1 : Level 1 - Loft[4]
Space.1.1 : Entrance - Common Space[2]
Space.5.1 : Level 4- Loft[11]
Space.4.1 : Level 3 - Loft[8]
Space.6.1 : Penthouse - Common Space[9]
Space.3.2 : Level 2 - Loft[6]
Space.1.2 : Pilotis - Common Space[1]
Space.5.2 : Level 4- Common Space[10]
Space.4.2 : Level 3 - Common Space[7]
Space.2.2 : Level 1 - Common Space[3]
Default

Space.1.1 : Entrance - Common Space[2]

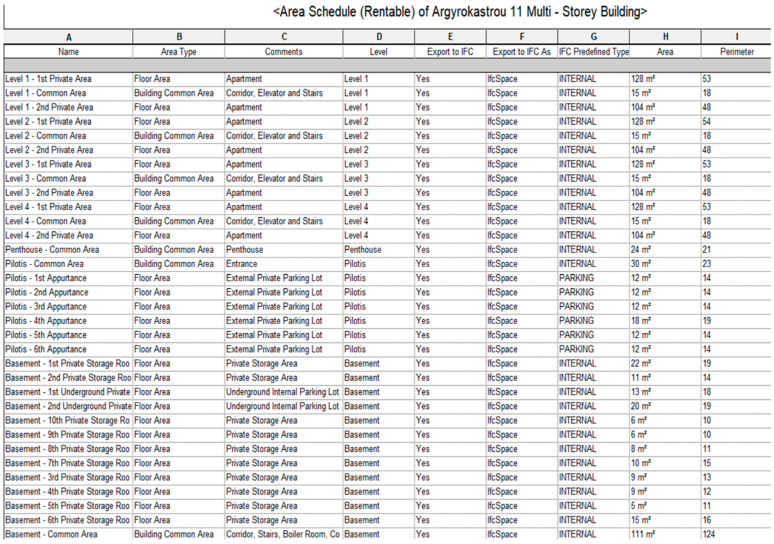
| Property | Value |
|---|---|
| Model | 7 |
| Discipline | Building Services |
| Name | Entrance - Common Space |
| Number | 2 |
| Type | Entrance - Common Space 2 |
| Type Name | Entrance - Common Space 2:397728 |
| Predefined Type | NOTDEFINED |
| Object Type | |
| Element Type | |

Welcome to Solibri Anywhere

**Figure 7.** Three-dimensional property unit of a commonly owned entrance.

**Figure 8.** Restrictions.

Figure 9 shows an inventory with geometric and semantic information for each 3D property unit.



<Area Schedule (Rentable) of Argyrokastrou 11 Multi - Storey Building>

| A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|
| Name | Area Type | Comments | Level | Export to IFC | Export to IFC As | IFC Predefined Type | Area | Perimeter |
| Level 1 - 1st Private Area | Floor Area | Apartment | Level 1 | Yes | IfcSpace | INTERNAL | 128 m² | 53 |
| Level 1 - Common Area | Building Common Area | Corridor, Elevator and Stairs | Level 1 | Yes | IfcSpace | INTERNAL | 15 m² | 18 |
| Level 1 - 2nd Private Area | Floor Area | Apartment | Level 1 | Yes | IfcSpace | INTERNAL | 104 m² | 48 |
| Level 2 - 1st Private Area | Floor Area | Apartment | Level 2 | Yes | IfcSpace | INTERNAL | 128 m² | 54 |
| Level 2 - Common Area | Building Common Area | Corridor, Elevator and Stairs | Level 2 | Yes | IfcSpace | INTERNAL | 15 m² | 18 |
| Level 2 - 2nd Private Area | Floor Area | Apartment | Level 2 | Yes | IfcSpace | INTERNAL | 104 m² | 48 |
| Level 3 - 1st Private Area | Floor Area | Apartment | Level 3 | Yes | IfcSpace | INTERNAL | 128 m² | 53 |
| Level 3 - Common Area | Building Common Area | Corridor, Elevator and Stairs | Level 3 | Yes | IfcSpace | INTERNAL | 15 m² | 18 |
| Level 3 - 2nd Private Area | Floor Area | Apartment | Level 3 | Yes | IfcSpace | INTERNAL | 104 m² | 48 |
| Level 4 - 1st Private Area | Floor Area | Apartment | Level 4 | Yes | IfcSpace | INTERNAL | 128 m² | 53 |
| Level 4 - Common Area | Building Common Area | Corridor, Elevator and Stairs | Level 4 | Yes | IfcSpace | INTERNAL | 15 m² | 18 |
| Level 4 - 2nd Private Area | Floor Area | Apartment | Level 4 | Yes | IfcSpace | INTERNAL | 104 m² | 48 |
| Penthouse - Common Area | Building Common Area | Penthouse | Penthouse | Yes | IfcSpace | INTERNAL | 24 m² | 21 |
| Pilotis - Common Area | Building Common Area | Entrance | Pilotis | Yes | IfcSpace | INTERNAL | 30 m² | 23 |
| Pilotis - 1st Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 12 m² | 14 |
| Pilotis - 2nd Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 12 m² | 14 |
| Pilotis - 3rd Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 12 m² | 14 |
| Pilotis - 4th Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 18 m² | 19 |
| Pilotis - 5th Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 12 m² | 14 |
| Pilotis - 6th Appurtance | Floor Area | External Private Parking Lot | Pilotis | Yes | IfcSpace | PARKING | 12 m² | 14 |
| Basement - 1st Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 22 m² | 19 |
| Basement - 2nd Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 11 m² | 14 |
| Basement - 1st Underground Private | Floor Area | Underground Internal Parking Lot | Basement | Yes | IfcSpace | INTERNAL | 13 m² | 18 |
| Basement - 2nd Underground Private | Floor Area | Underground Internal Parking Lot | Basement | Yes | IfcSpace | INTERNAL | 20 m² | 19 |
| Basement - 10th Private Storage Ro | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 6 m² | 10 |
| Basement - 9th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 6 m² | 10 |
| Basement - 8th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 8 m² | 11 |
| Basement - 7th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 10 m² | 15 |
| Basement - 3rd Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 9 m² | 13 |
| Basement - 4th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 9 m² | 12 |
| Basement - 5th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 5 m² | 11 |
| Basement - 6th Private Storage Roo | Floor Area | Private Storage Area | Basement | Yes | IfcSpace | INTERNAL | 15 m² | 16 |
| Basement - Common Area | Building Common Area | Corridor, Stairs, Boiler Room, Co | Basement | Yes | IfcSpace | INTERNAL | 111 m² | 124 |

**Figure 9.** Three-dimensional property unit inventory.

Figure 10 presents the open-source code of TimeGAN that produces the AI sensors and the time series simulative data.

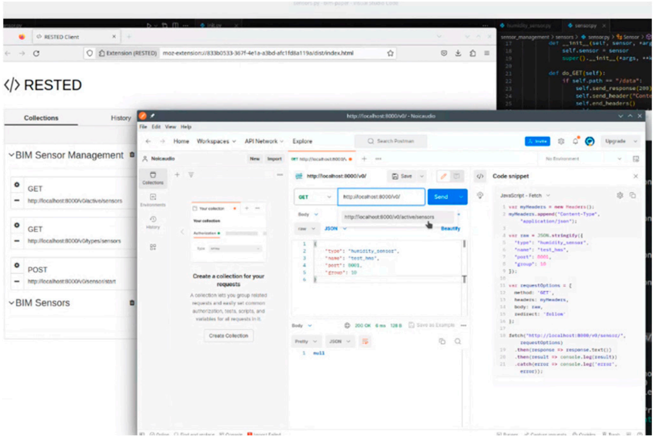
```
python3 main_timegan.py --data_name stock --seq_len
24 --module gru
--hidden_dim 24 --num_layer 3 --iteration 50000 --
batch_size 128
  --metric_iteration 10
```

**Figure 10.** Open-source snippet of code that produces the simulative time series datasets.

Figure 11 presents the way that the sensor information is stored in the MongoDB database. Figures 12 and 13 show the web interface for programming and managing the sensors.

{ “name”: “capacity sensor”, “capacity”: “100”, “pressure”: null}

**Figure 11.** Examples of the MongoDB database.



moz-extension://833b0533-367f-4e1a-a3bd-afc1fd8a119a/dist/index.html

GET http://localhost:8000/v0/active/sensors

GET http://localhost:8000/v0/types/sensors

POST http://localhost:8000/v0/sensor/start

http://localhost:8000/v0/ - Noicaudio

GET http://localhost:8000/v0/

http://localhost:8000/v0/active/sensors

```
{
    "type": "humidity_sensor",
    "name": "test_hms",
    "port": 8001,
    "group": 10
}
```

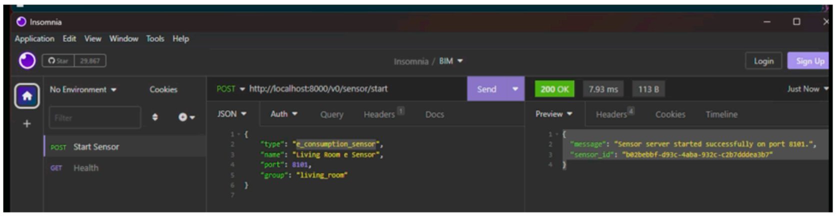
200 OK 6 ms 128 B

```
null
```

```
var myHeaders = new Headers();
myHeaders.append("Content-Type",
    "application/json");

var raw = JSON.stringify({
  "type": "humidity_sensor",
  "name": "test_hms",
  "port": 8001,
  "group": 10
});

var requestOptions = {
  method: 'GET',
  headers: myHeaders,
  body: raw,
  redirect: 'follow'
};

fetch("http://localhost:8000/v0/sensor/",
    requestOptions)
  .then(response => response.text())
  .then(result => console.log(result))
  .catch(error => console.log('error',
    error));
```

```
sensor_management > sensors > sensor.py > Sensor >
    def __init__(self, sensor, *ar
        self.sensor = sensor
        super().__init__(*args, **

    def do_GET(self):
        if self.path == "/data":
            self.send_response(200
            self.send_header("Conte
            self.end_headers()
```

**Figure 12.** The web interface for managing and storing sensors.



POST http://localhost:8000/v0/sensor/start

```
{
    "type": "e_consumption_sensor",
    "name": "Living Room e Sensor",
    "port": 8101,
    "group": "living_room"
}
```

```
{
  "message": "Sensor server started successfully on port 8101.",
  "sensor_id": "b02bebbf-d93c-4aba-932c-c2b7dddea3b7"
}
```

**Figure 13.** Programming the "electronic consumption sensor".

The DT of the neighborhood is presented through a wide array of dynamic effects and artificial options such as the configuration of wind intensity and direction, movement of clouds, reflection of puddles, movement of fallen leaves, and water streaming (Figure 14). Sounds are also added in the model, adding a deeper layer of realism, i.e., the sound of water being sprayed from a sink, a doorbell or alarm ringing, birds chirping, etc. (Figure 15).

**Figure 14.** Dynamic water effect with corresponding sound effect.

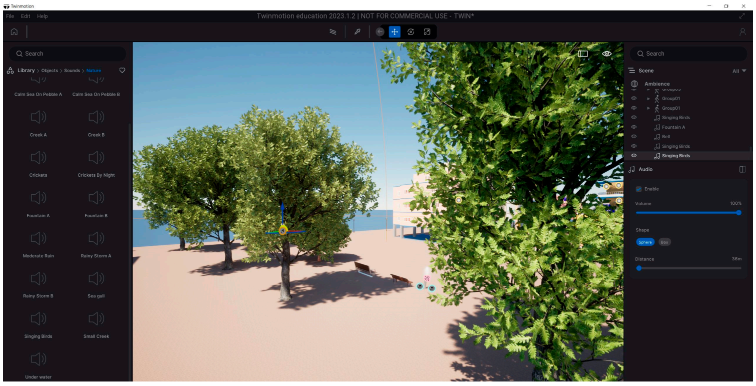


**Figure 15.** Configuration panel for adding sound effects.

The neighborhood is visualized under realistic and simulated weather effects and conditions. A seamless and quick change between sunny, rainy, and snowy weather can be made, as shown in Figure 16, while mixed conditions can also be created, i.e., sleet or sun with rain, as shown in Figure 17. The intensity of each weather effect can also be adjusted (Figure 18). All seasonal conditions from summer, fall, winter, and spring are interchangeable (Figure 19) while the unique behavior of the various elements of the neighborhood is presented, i.e., how the lighting poles are going to be turned on or off according to the time of day (Figure 20).

**Figure 16.** Interchange of the various weather conditions.

**Figure 17.** Mixed weather conditions such as sunny with rain.

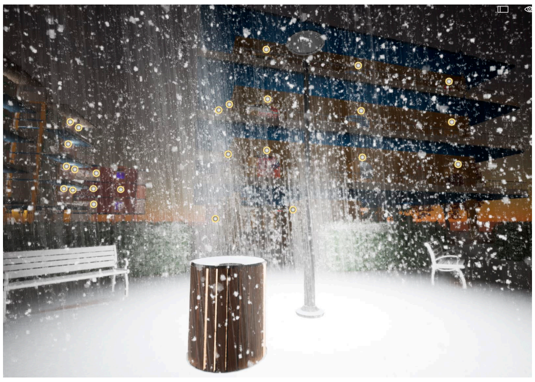


**Figure 18.** Intense snow.

**Figure 19.** Passing of seasons.

**Figure 20.** The lights turn on at night.

The configuration of different times of day, simulating the 24 h of the day according to the different conditions of each season, is also possible (Figure 21).

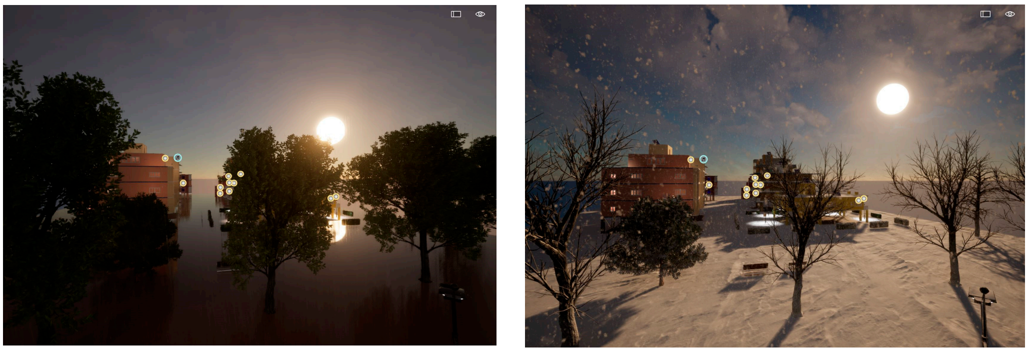


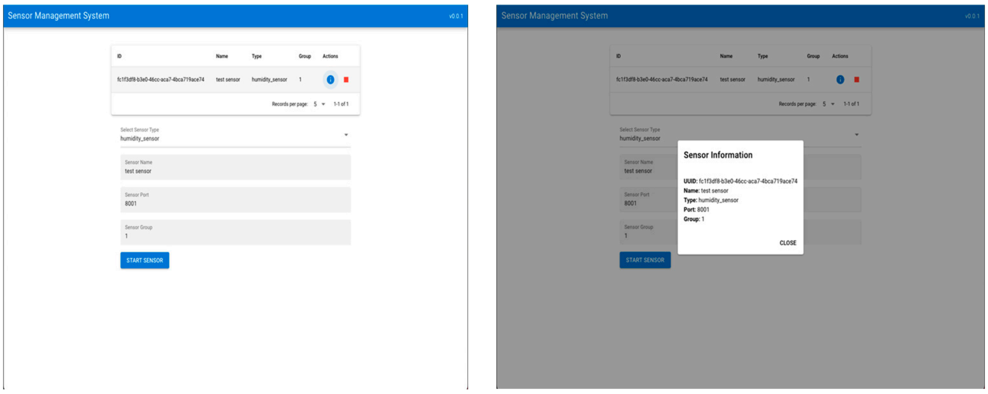
**Figure 21.** Change in the time of day.

## 5. Results

### *5.1. Results of the AI–BIM Compilation*

#### 5.1.1. Sensor Management Platform

The SM platform is the primary data source for the DABIM platform as its synthetic IoT sensor network produces vast time series data for the individual devices of each building for the entirety of the neighborhood under study. These datasets are captured by the DABIM platform which also captures the entailed data of the IFC schemas. The datasets are processed, enabling further analyses of sustainable suggestions and scenarios through machine learning algorithms. IfcOpenShell enables the seamless integration of the constructed BIM models, which is the cornerstone of the first part of this broader research. The sensor data gain spatial information and are more adept at understanding the energy patterns of each 3D household space. The cloud-based MongoDB database enables the data to be highly scalable and available. Real-world simulative sensor data, detailed BIMs enriched with 3D property units, and machine learning analyses are merged into one homogenous proposal that aspires to support cadastral reformation in the future. The SM platform enables the seamless, easy, and engaging interaction of the user with sensors through a web-based UI. The user can view details on the operation of the sensors, such as the sensor's type, ID, actions, and group, as well as managing its saving port and starting or halting its tracking activities or even deleting it entirely (Figure 22).



| ID | Name | Type | Group | Actions |
|---|---|---|---|---|
| fc1f3df8-b3e0-46cc-aca7-4bca719ace74 | test sensor | humidity_sensor | 1 | ● ■ |

Select Sensor Type: humidity_sensor
Sensor Name: test sensor
Sensor Port: 8001
Sensor Group: 1

Sensor Information

**UUID:** fc1f3df8-b3e0-46cc-aca7-4bca719ace74
**Name:** test sensor
**Type:** humidity_sensor
**Port:** 8001
**Group:** 1

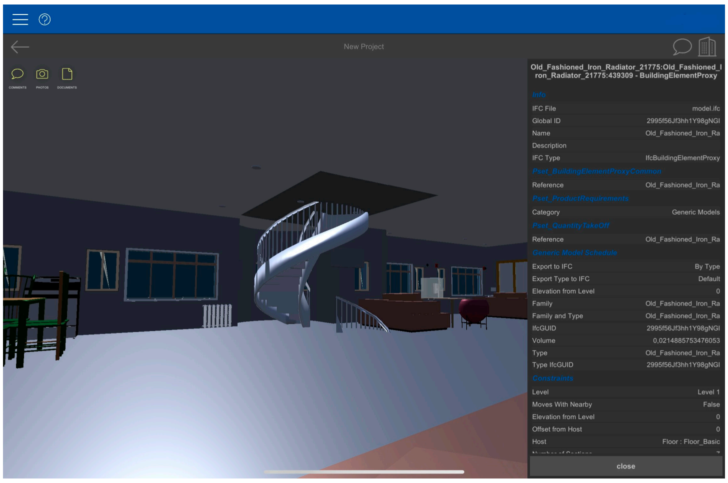
**Figure 22.** Interaction with the humidity sensor in the interface.

### 5.1.2. Data Analysis—BIM Platform

Data Analysis and BIM visualization platform:

1. Receives the datasets from the SM platform, enabling the DABIM platform to leverage data from the IFC schemas that otherwise would be inaccessible;
2. Captures, aggregates, and cleans the AI-generated sensor datasets of the various devices of the BIMs;
3. Processes the IFC files of the BIMs that are augmented with the AI-based sensors and stores the time series data into the document-based database in MongoDB format;
4. Prepares the data for machine learning applications such as forecasting, anomaly detection, and decision trees for providing future energy expenditure, cost-saving, and scenario suggestions tailored to each household.

All in all, the DABIM platform is an interactive interface that enables a full view of the outside and inside of the BIMs (Figure 23) while presenting a complete IFC schema for management (Figure 24). It allows interaction with all the architectural and structural elements of the buildings and viewing of their properties, while the user can also upload pictures and other desired file formats (Figure 25).



Old_Fashioned_Iron_Radiator_21775:Old_Fashioned_Iron_Radiator_21775:439309 - BuildingElementProxy

| | |
|---|---|
| *Info* | |
| IFC File | model.ifc |
| Global ID | 2995f56Jf3hh1Y98gNGI |
| Name | Old_Fashioned_Iron_Ra |
| Description | |
| IFC Type | IfcBuildingElementProxy |
| *Pset_BuildingElementProxyCommon* | |
| Reference | Old_Fashioned_Iron_Ra |
| *Pset_ProductRequirements* | |
| Category | Generic Models |
| *Pset_QuantityTakeOff* | |
| Reference | Old_Fashioned_Iron_Ra |
| *Generic Model Schedule* | |
| Export to IFC | By Type |
| Export Type to IFC | Default |
| Elevation from Level | 0 |
| Family | Old_Fashioned_Iron_Ra |
| Family and Type | Old_Fashioned_Iron_Ra |
| IfcGUID | 2995f56Jf3hh1Y98gNGI |
| Volume | 0,0214885753476053 |
| Type | Old_Fashioned_Iron_Ra |
| Type IfcGUID | 2995f56Jf3hh1Y98gNGI |
| *Constraints* | |
| Level | Level 1 |
| Moves With Nearby | False |
| Elevation from Level | 0 |
| Offset from Host | 0 |
| Host | Floor : Floor_Basic |

**Figure 23.** Internal navigation of a modelled BIM.

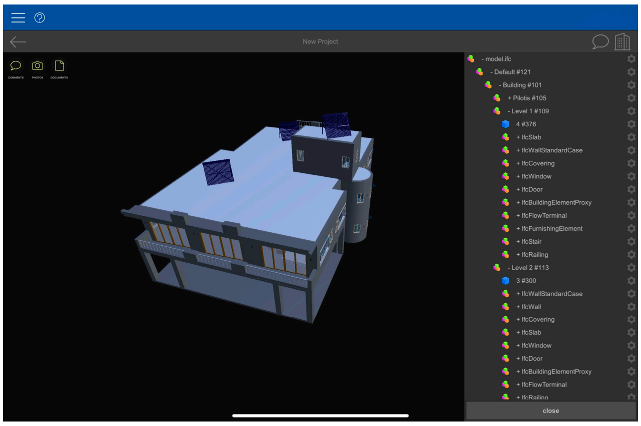
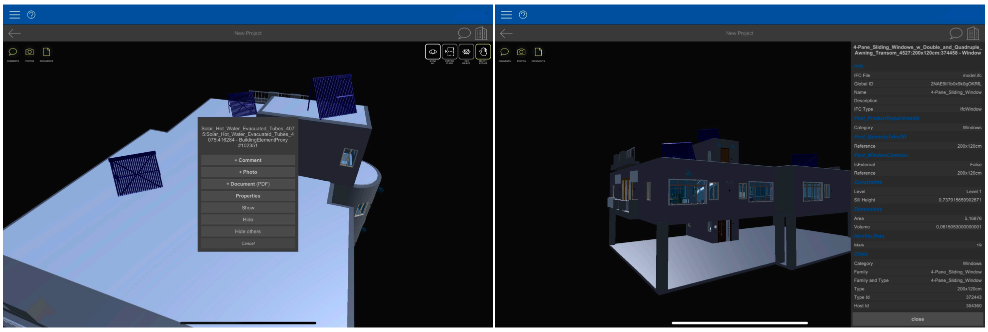


**Figure 24.** The entire IFC schema on the right.



**4-Pane_Sliding_Windows_w_Double_and_Quadruple_Awning_Transom_4527:200x120cm:374458 - Window**

*Info*

| | |
|---|---|
| IFC File | model.ifc |
| Global ID | 2NAE9Il1b0x9k0gOKRfL |
| Name | 4-Pane_Sliding_Window |
| Description | |
| IFC Type | IfcWindow |

*Pset_ProductRequirements*

| | |
|---|---|
| Category | Windows |

*Pset_QuantityTakeOff*

| | |
|---|---|
| Reference | 200x120cm |

*Pset_WindowCommon*

| | |
|---|---|
| IsExternal | False |
| Reference | 200x120cm |

*Constraints*

| | |
|---|---|
| Level | Level 1 |
| Sill Height | 0,737915659902671 |

*Dimensions*

| | |
|---|---|
| Area | 5,16876 |
| Volume | 0,0615053000000001 |

*Identity Data*

| | |
|---|---|
| Mark | 19 |

*Other*

| | |
|---|---|
| Category | Windows |
| Family | 4-Pane_Sliding_Window |
| Family and Type | 4-Pane_Sliding_Window |
| Type | 200x120cm |
| Type Id | 372443 |
| Host Id | 354360 |

**Figure 25.** Interactive options of the platform.

## *5.2. Results of the Machine Learning Algorithms for Optimal Household Management*

### 5.2.1. Forecasting

Forecasting is a machine-learning-empowered technique of predicting how the values of certain datasets are going to behave in the short or long term. This machine learning algorithm is used for predicting the energy consumption of households and to carry out cost estimations. Forecasting is achieved by utilizing the Auto-Regressive Integrated Moving Average (ARIMA) model, which is the generalization of an auto-regressive mobbing average (ARMA) model. ARIMA tackles three pillars of forecasting and predicting:

1. Trend: a continuous occurrence for a long period of time;
2. Seasonality: an event that appears only during specific periods and conditions;
3. Randomness: an occurrence that cannot be predicted and takes place out of order.

These aforementioned parameters can be presented and noticed in the generated data of the neighborhood under study. For the energy consumption of the BIM under study, these factors could mean:

1. Trend: summer increases energy consumption;
2. Seasonality: during the weekends, energy consumption can decrease as more people are off on vacation and outings or at the beach;
3. Randomness: a rainstorm may hit, causing energy consumption values to drop due to the reduction in temperature; air conditioning units are not going to be operating as much as before.

This scenario can be tackled for the designed dataset by utilizing the ARIMA model:

1. Auto-Regressive: This part of the ARIMA model processes the relevance of the current energy consumption values compared to the values of the past days. In the case of a heatwave, the model expects that the energy consumption values are going to continue being high for a while longer;

2. Integrated: This function captures the trend, i.e., at the beginning of the summer season, the model expects that the sudden rise in energy expenditure values is going to continue for the upcoming weeks;
3. MovingAverage: This parameter simulates a weather radar, capturing unexpected events, i.e., rainstorms. ARIMA can adjust its predictions according to sudden changes in the normalized values.

Below is a graph that showcases the forecast for the behavior of the various devices in the BIMs regarding energy consumption in the period from June to September 2020. The graph is crafted by feeding results from the AI-generated sensors, simulating real conditions for the area under study (Figure 26).

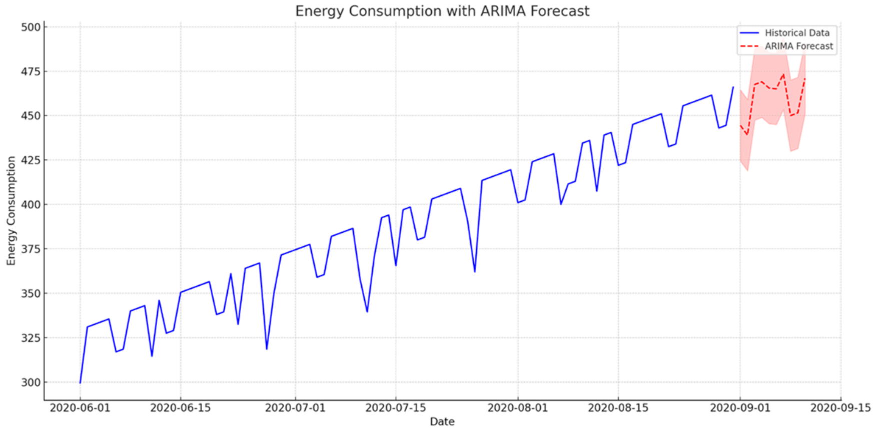


**Figure 26.** Simulation of the energy consumption of the neighborhood using the ARIMA forecast model.

The blue continuous line represents the historical data while the red dashed line is the forecast of the ARIMA model. Therefore, the proposal offers possible simulations and future predictions of the energy consumption of each modelled household in the Digital Twin of the neighborhood.

### 5.2.2. Anomaly Detection through Isolation Forest

Anomaly Detection models are machine learning models that are used for discerning anomalies inside a dataset. Isolation Forest has been developed [52] and is an algorithm for data anomaly detection. The basis of the Isolation Forest approach is the utilization of binary trees. Isolation Forest can be implemented in the neighborhood under study if the building is viewed as individual trees while the entirety of the neighborhood comprises a forest. Most of the individual buildings or trees follow specific and similar patterns of energy consumption and device usage. Most of the buildings (trees) consume similar amounts of resources, i.e., electricity, making them the norm or the regular trees. However, there are odd houses or odd trees that present higher values of energy consumption and resource expenditure. The isolation forest algorithm quickly discovers the odd ones, saving important amounts of time.

The upper diagram has been created by feeding it the generated data of the AI-generated sensors of the neighborhood under study (Figure 27). The red crosses mark the anomalies that are detected through the functionality of the sensors from June to September 2020. The first and last anomalies can be omitted as they represent the first and last time that the model received data, respectively. The biggest anomalies are detected during the beginning of July and August, respectively. Therefore, the proposal offers anomaly detection regarding the functionality of each device and system inside the BIMs.

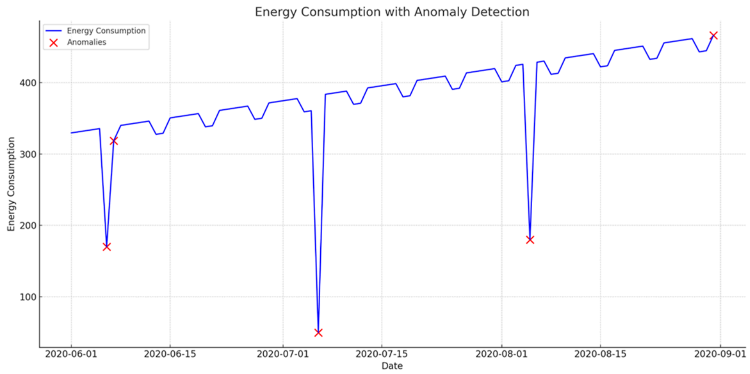


**Figure 27.** Simulation of detecting anomalies in the crafted dataset of the AI-generated sensors.

### 5.2.3. Decision Trees for Scenario Production and Suggestions

Decision Trees entail a decision-making technique that can be used to reach multiple desired outputs based on a set of inputs. The diagram is simulated like a tree, abundant with branches. The root of each tree represents the posed question at the time while each branch represents a different alternative solution. After the first choice is made, another dual branch with two stems appears. The input and output procedures are continued under a loop until the desired outcome is reached. For the simulation of decision-making and scenario-crafting for the neighborhood under study a specific decision has been created for each device. Through various inputs and personal preferences, each user that utilized the DABIM platform is going to be able to receive suggestions based on Decision Trees for energy consumption scenarios.

The below diagram in Figure 28 aids the user in making decisions about the expenditure of an air-conditioning unit for minimizing costs and saving energy. Therefore, the proposal enables optimal decision-making and scenario-construction options for each device in every 3D household of the neighborhood.

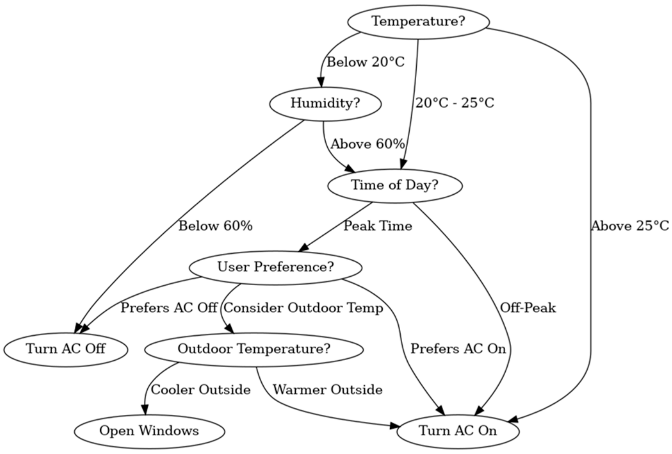


**Figure 28.** Created Decision Tree diagram for managing the usage of air-conditioning units.

## 6. Conclusions—Assessment

This method highlights the interoperability of the IFC standard and BIM models with coding and ML algorithms for creating and monitoring a DT of an urban neighborhood. Through this method, each individual device gains intelligence. This methodology offers a low-cost twin of the neighborhood, without additional field work, for simulating weather and environmental conditions that receive real data from the official weather observatory. Through the various utilized ML algorithms of Decision Trees, Anomaly Detection, and Isolation Forest, the proposal presents a better understanding of energy consumption patterns with the possibilities of predicting possible device expenditure and detecting anomalies and odd cases of energy consumption, as well as aiding in optimal decision-making. The AI-generated sensors that are chosen to be created and utilized in this research offer some unique characteristics, such as:

1. Being highly customizable and modular;
2. Enabling qualitative, scalable, and realistic datasets that can be utilized for 4D cadastral and urban management applications;
3. They require no fieldwork;
4. Being able to generate vast real-time datasets that obtain information from real locations and open-source weather conditions;
5. Having a simple structure that can be modeled and supervised easily while being adaptable to multiple coding standards.

The biggest challenge of the methodology is the training procedure of the AI model as it needs to be fed with extensive, accurate, and sufficient data that cover a plethora of possible scenarios and combinations that can happen in the real world. It requires rigorous studying of the IFC standard and its structure, as well as understanding which classes are important and which are not. The Greek cadastral legislation is also thoroughly studied to teach the model how to correctly store the various 3D property units. Extensive research of real weather and environmental conditions is also conducted, as well as a detailed study of manufacturer standards and qualifications of device functionality. Researching extensively, filtering the various information, merging the necessary data, and feeding them to the AI model is the most challenging task of the entire methodology.

Consequently, all the research questions have been answered as the DT of the neighborhood hosts, in one homogenous cloud-based and user-friendly environment, 3D cadastral information, energy consumption monitoring, and environmental simulations for both existing and new BIMs. Therefore, the proposal merges 3D cadastral visualization with 4D, 5D, and 6D simulations.

## 7. Future Research

The method may be improved in future to support:

1. Four-dimensional, 5D, and 6D crowdsourcing urban and land management procedures;
2. Sustainability frameworks for reducing energy consumption in centers;
3. Cost-saving campaigns with rewards;
4. Low-cost applications for replacing old devices with new and smart ones;
5. The creation of a realistic and accurate Digital Twin of an urban neighborhood;
6. Modernized cadastral applications;
7. Platforms for IoT research and urban planning.

The DT of the neighborhood could implement a cadastral database according to the new LADM II standard that is going to entail 3D spatial profiles of the various 3D property units and also support a detailed 3D representation of the entailed RRRs. Another future addition that can be supported by the LADM II is the inclusion of valuation information about each 3D property unit that could also be empowered by AI and ML algorithms. Three-dimensional land use visualization is also another possible addition. This would result in the DT being fully equipped with 3D cadastral, legal, land use, and valuation information. The methodology can also be spatially expanded in order to cover a broader and more complex urban area with the interchange of complicated legal rights, intertwined building structures, and interchanged land uses. The proposal could also be properly adjusted for empowering a policy for installing new MEP and HVAC devices. The APIs and platforms could also be converted to mobile applications for portable, easy, and quick energy consumption and household tracking. Lastly, gamification incentives could be implemented to the overall methodology and reward the owner/tenant with the lowest energy consumption value. This methodology is highly expendable and adjustable, making it applicable to many case scenarios. It can be modified in the future to implement the newest technology and AI trends. It can incorporate more ML analytics for different purposes, as well as real-time analytics and notifications for more immediate interventions and tracking.

**Author Contributions:** Conceptualization, C.P. and D.A.; methodology, C.P. and D.A.; software, C.A.; validation, C.P.; formal analysis, C.P. and D.A.; investigation, C.P., D.A. and C.A.; resources, C.A. and D.A.; data curation, C.A. and D.A.; writing—original draft preparation, D.A. and C.A.; writing—review and editing, C.P.; visualization, D.A.; supervision, C.P.; project administration, C.P. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The raw data supporting the conclusions of this article will be made available by the authors on request.

**Conflicts of Interest:** Author Chrystos Alexiou was employed by the company Dalekdyne Inc. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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